INTRODUCTION

SMP Challenge Summary: Social Media Prediction Challenge

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Abstract

SMP Challenge is an annual challenge that seeks top research teams to develop innovative forecasting methods that can enhance social and business applications. We define and introduce the Social Media Popularity Prediction (SMPP) task that predicting the future popularity of a post made by a specific user at a given time on social media. This task is pivotal in various applications and scenarios, such as online advertising, social recommendations, post ranking, and demand forecasting, etc. To motivate diverse perspectives of social media prediction researches, we built a large-scale benchmark Social Media Prediction Dataset (SMPD) that includes approximately 500K posts, along with associated 756 tags, visual-language data, and spatial-temporal information, and sourced from around 70K users and their profiles.

With participation and contribution from top teams worldwide, the challenge has seen continuous performance improvements in recent years, driven by technological advancements. For the latest information, leaderboard or online evaluation, please visit the SMP Challenge Homepage: www.smp-challenge.com.

CCS Concepts

• Information systems → Web searching and information discovery; **Multimedia information systems**; **• Computing methodologies → Computer vision tasks**; **Natural language processing**.

Keywords

Social Multimedia, Popularity Prediction, Multimodal Learning

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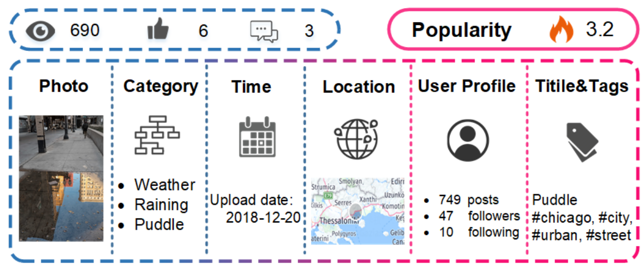

Figure 1: Task: Social Media Popularity Prediction [29].

1 Introduction

Social media is one of the popular content sharing and go-to marketing channels for our life and businesses worldwide, whether you're looking to share the individual opinions, expand connections, demonstrate the value of social media to decision-makers or investigate upcoming trends [1, 25]. There are estimated to be 5.17 billion total social media users worldwide now, with an average person using 6.7 different social networks per month, and social media advertising spend is projected to reach $219.8 billion in 2024 [28]. As a result, social media prediction has emerged as a crucial area of focus [33], emphasizing forecasting tasks that drive various modern digital applications for online media platforms, brand marketers, social influencers, and individuals. These efforts not only enhance user experiences but also improve business strategies for both present and future needs, which supports a wide range of applications [7, 8, 19, 23, 24, 36], such as online advertising, social recommendations, post ranking, and demand forecasting.

The SMP Challenge (Social Media Prediction Challenge) [29, 32] is an annual competition focused on discovering innovative solutions for forecasting problems. Research in social media prediction has already encompassed key areas in multimedia and artificial intelligence, while also connected the fields such as social computing, computer vision, and natural language processing. Simultaneously, with the global ubiquity of social media, research interest has increasingly turned toward exploring rich social contexts and knowledge through multimodal information or interactions, such

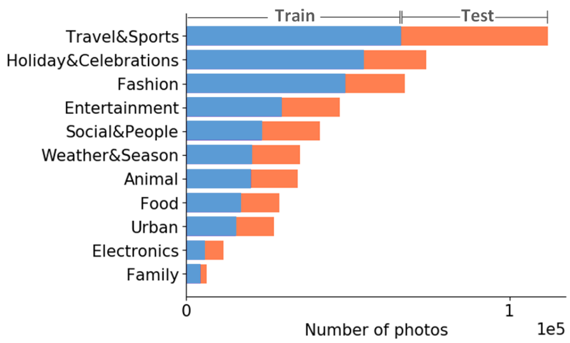

Figure 2: The post topic distribution and the data splits.

as images, text, video, and events. Our key highlights can be summarized as follows:

- We propose the task Social Media Popularity Prediction, which focuses on predicting the upcoming popularity of an online post via rich and diverse multimodal, temporal-spatial content and user profile on social media
- We built the Social Media Prediction Dataset, a large-scale, multimodal dataset includes 70K users and 500K online posts, with topic tags, user profiles, vision-language metadata, and the attention or interaction information.
- Following our proposal of several temporal and multimodal learning methods, the challenge attracted over worldwide research teams or companies.

2 Problem Definition

However, the vast amount of online content often leads to information overload, making it challenging to discover relevant news, emerging topics, and noteworthy products. Online word-of-mouth has become a vital tool for efficiently navigating this sea of information. We introduce the task of Social Media Popularity Prediction (SMPP), which focuses on predicting the popularity of an online post on social media [30, 31, 33].

Specifically, the task involves predicting the social media popularity, denoted as s, of a new post v from a user u if it were published at a specific time t. Consider a set of n triplet data user-post-time in social media streams, each user-post pair (u, v) associated with a specific sharing time t. The sequence of user-post can be represented as $S = \{(u_1, v_1), (u_2, v_2), \ldots, (u_n, v_n)\}$, ordered by their sharing times such that $t_1 \leq t_2 \leq \cdots \leq t_n$. The popularity score represents the level of interactions the post receives on a social media platform, such as views, likes, and clicks (e.g., view counts on Flickr, Pin counts on Pinterest, or relevant metrics). In our challenge, we use "view count" as the primary metric for post popularity, though this definition can be broadened to include other forms of engagement. The distribution of log-normalized popularity values [31] shows the large variations among different posts (e.g. varies from zero to millions). To achieve this goal, participating teams need to develop new algorithms or models that automatically predict post popularity by considering post content, posting time, and various multimedia information within a time-sensitive dynamics [17, 35].

Table 1: SMPD: Statistical Summary of the Dataset.[32]

Metrics	Statistics	
	Train	Test
Number of Posts	3.05×10^5	1.81×10^5
Average Popularity of Posts	6.41	5.12
Number of users	3.8×10^4	3.1×10^4
Temporal Coverage of Posts	480 days	
Number of custom tags	2.5×10^5	
Number of 3^{rd} level categories	668	

3 Dataset Overview

We developed the SMPD (Social Media Prediction Dataset) [29] [1], a large-scale, multimodal dataset comprising approximately 70K users and 500K online posts, with temporal popularity data spanning over 500 days. Our aim is to make the challenge dataset as diverse and comprehensive as possible, accurately reflecting the complexity of the "social media worl". The dataset includes user profiles, multimodal metadata, and 756 category tags and captures the social media post popularity and corresponding timestamps. We divide the data into chronological splits, organized by date and time. Participating teams are tasked with developing innovative algorithms or solutions to improve predictions on streaming data.

4 Evaluation

For objective evaluation, we assess the performance of submitted methods on the unpublished SMPD test set. We use a combination of Spearman's Rank Correlation (SRC or Spearman's Rho) and Mean Absolute Error (MAE) to provide quantitative and objective assessments of the models' performance. The competition ranking is determined by an objective evaluation method. Teams are ranked based on performances of specific metrics, and their overall ranking is derived by combining individual rankings in a balanced manner.

5 Research Progress

Early social media prediction methods primarily focused on areas such as feature selection [2, 13, 16, 20], deep neural networks [6], and model ensembling [9]. These approaches shared challenges common to mainstream deep learning tasks but often overlooked the higher-level complexities specific to social media prediction. In recent years, novel ideas have emerged, motivated by embedding learning [6, 18, 22, 27], semantic learning [10, 14], user-post interaction learning [2, 11], and the visual-textual multimodal learning. These methods have begun to uncover the inherent characteristics of social media data by addressing high-level correlations. Techniques such as attention mechanisms, recurrent networks, and sliding window models [3–5, 14, 34] have led to performance improvements. This year solutions introduce several new directions compared to previous studies [12, 15, 21, 26], including vision-language contrastive or collaborative learning, semantic alignment, dual-stream transformer, or high-order adaptation, etc. The winning team achieved the highest SRC and MAE scores, surpassing previous years' first-place results. Notably, the best SRC performance improved by 10%. These are meaningful and important progresses.

[1] http://smp-challenge.com/dataset

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